Chapter 2

Theoretical Background

Abstract

This chapter provides the theoretical background of common gait disorders and advancements in wearable technology for gait analysis. It also introduces key concepts in signal processing, feature extraction, and wavelet transforms. A comprehensive literature review on the role of EEG in BCI, EMG in gait analysis, and integration of EMG and EEG for BCI application is also presented, highlighting recent research and applications in these fields.

2.1 Introduction

The sensors employed in human activity monitoring come with unique characteristics depending on the type of signal recorded and its placement on the body (Regterschot et al., 2021). Inertial measurement units (IMUs), for instance, are prevalent in sports science and rehabilitation settings, facilitating the monitoring movement patterns, balance, and coordination across different activities (Badawi et al., 2020). Force-sensitive resistors are used extensively in foot insole applications, offering valuable insights into pressure distribution and gait analysis (Negi et al., 2022). Further, EEG and EMG sensors are crucial in understanding neural and muscular dynamics. EEG sensors, vital for monitoring brain activity, have become central in BCI research (Gwin and Ferris, 2012). EMG sensors are crucial for recording and analyzing muscle activity, assisting in rehabilitation, sports science, and prosthetics. (Wang et al., 2021; Caffi et al., 2022). The rapid advancements in machine learning and deep learning have garnered significant attention from researchers worldwide, especially in utilizing sensor data (Gil-Martín et al., 2021). This chapter extensively reviews the literature on gait abnormalities, gait analysis using wearable sensors, signal processing techniques, EEG and EMG's role in fields like BCI and gait analysis, and an introduction to deep learning.

2.2 Gait Abnormalities

Gait abnormalities can arise from neurological disorders, musculoskeletal injuries, and other conditions, leading to rhythm, speed, symmetry, and coordination disturbances (Verghese et al., 2005). Neurological disorders such as Parkinson's disease, Huntington's, and Amyotrophic Lateral Sclerosis (ALS) can significantly impact gait patterns by causing issues with motor control, muscle strength, and coordination (Mahlknecht et al., 2013). Parkinson's disease, is characterized by reduced speed, shortened steps, and impaired balance, affecting the overall rhythm and symmetry of walking (Hausdorff, 2009). Musculoskeletal injuries, such as osteoarthritis and rheumatoid arthritis, can also contribute to gait abnormalities by causing pain, stiffness, and joint deformities that alter the biomechanics of walking (Jin et al., 2019).

2.2.1 Neurological Gait Abnormalities

One class of disease that most impacts locomotion are neurodegenerative diseases (NDDs). NDD is a broad term for diseases affecting various brain functions like memory, motor activities, and cognition (Gitler et al., 2017). With no potent cure available, NDDs are one of the common causes of mortality and morbidity in the elderly (Heemels, 2016). Common neurodegenerative diseases are Alzheimer's disease, Parkinson's disease, Huntington's disease, and Amyotrophic Lateral Sclerosis (ALS). A common neurological illness is Alzheimer's disease. It progresses slowly and presently has no effective therapy (Zetterberg and Bendlin, 2021). Parkinson's disease is a prevalent neurodegenerative condition characterized by synuclein build-up in Lewy bodies. Parkinson's disease is caused by environmental and hereditary factors (Vázquez-Vélez and Zoghbi, 2021). Creutzfeldt-Jakob disease (CJD) is a quickly progressing, deadly neurodegenerative condition mainly caused by a mutant isoform of a cellular glycoprotein called a prion (Iwasaki, 2017). The progression of CJD is rapid, and generally, the death occurs within a year (Sikorska et al., 2012). Progressive supranuclear palsy (PSP) is an illness causing slow degeneration and death of specific brain regions. Its symptoms include loss of balance, slow movement, trouble moving the eyes, and cognitive impairment (Globe et al., 1988). Pick's disease is a severe genetic neurodegenerative condition that most commonly affects the frontal and temporal poles (Dickson, 1998). Dysfunction, tremors, and ataxia characterize multiple system atrophy (MSA) due to the gradual degradation of neurons in various brain regions (Wenning et al., 2004). Amyotrophic lateral sclerosis is a progressive motor neuron disease involving muscle atrophy, neuronal motor loss, paralysis, and death (Mitchell and Borasio, 2007).

2.2.2 Non-Neurological Gait Abnormalities

Non-neurological gait abnormalities are often characterized by sluggish gait due to musculoskeletal constraints often caused by injuries. One condition affecting a large population is prolapsed intervertebral disc (PIVD), caused by disc displacement in the spine. Major symptoms of PIVD are pain, numbness, weakness in the affected region, and antalgic gait (Kelsey et al., 1990; Humphreys and Eck et al., 1990). A common autoimmune condition in the middle-aged population is rheumatoid arthritis (RA) (McInnes and Schett, 2011). It causes joint and tissue inflammation, leading to pain, stiffness, and trouble moving the afflicted joints. Gait characteristics of RA include antalgic gait, reduced walking speed, cadence, and stride length (Baan et al., 2012). Older people above the age of 60 often develop osteoarthritis, which is a degenerative joint condition in which the protecting cartilage on the ends of bones wears away over time, causing discomfort, stiffness, and swelling in joints, bone spurs, grating sensation, and difficulty in movement (Broström et al., 2012; Hamerman, 1989).

2.3 Gait Analysis Using Wearable Sensors

Gait abnormalities are multifaceted and can stem from neurological, musculoskeletal, and systemic conditions (Rahman et al., 2024). Analyzing gait patterns and abnormalities is critical in diagnosing and managing a wide range of health conditions, highlighting the significance of comprehensive assessment and tailored interventions to address these issues effectively (Borzelli et al., 2024). Gait analysis utilizing wearable sensors is a convenient and efficient approach to gathering valuable insights for health-related applications for both rehabilitation and diagnostic purposes. It is typically categorized into gait kinematics and gait kinetics (Tao et al., 2012). The kinematic system is employed to capture positional and orientational data, along with the angles of joints and the associated linear and angular velocities and accelerations (Abbass and Abdulrahman, 2013). Gait kinetics examines forces governing movement during walking, encompassing factors like gravity, inertia, joint reaction forces, ground reaction forces, and muscular contributions (Dicharry, 2010). Multiple sensor modalities are often combined to gain better insight into gait parameters. Table 2.1 presents a comprehensive list of wearable sensor-based gait analysis studies spanning diverse fields.

Table 2.1 Summary of studies involving different sensors for gait analysis.

Author (Year)	***Sensor***	***Application***
Breitman et al., (2023)	Force Plates and Video capture	Gait event identification
Ng and Andrysek., (2023)	Gyroscope	Classification of gait changes in lower leg amputee
Zhao et al., (2023)	Inertial Measurement Unit	Evaluation of hemiplegic gait
Negi et al., (2022)	Velostat based foot insole	Gait analysis
Shi et al., (2022)	Foot insole	Effect of contoured insoles on gait parameters in diabetic subjects.
Strutzenberger et al., (2022)	Foot Insole and Video Capture	Evaluation of gait parameters during incline and treadmill walking.
Apsega et al., (2020)	Inertial sensors	Frailty screening in older people.
Nutakki et al., (2020)	Accelerometer	Gait kinematic analysis
Terayama et al., (2018)	Triple-axial accelerometers	Assessment of ataxia due to spinocerebellar degeneration.
Wang et al., (2018)	Inertial sensor and film-pressure sensor	Estimation of the spatial-temporal gait parameters.

2.4 Signal Processing and Feature Extraction

Signal processing involves the extensive analysis and modification of a diverse range of signals, including sound, images, and scientific measurements (Zhang, 2022). It is critical in various fields, such as telecommunications, audio engineering, biomedical engineering, and data science. The core objective of signal processing is to transform raw data into a more useful form, often enhancing the quality, extracting valuable information, or making the data suitable for further analysis and interpretation (Cerutti, 2011). A fundamental task in signal processing is feature extraction, a process designed to capture and highlight the most relevant information contained within a signal. Feature extraction is a crucial step in signal processing, involving identifying and isolating specific characteristics or attributes from raw signal data that can reveal underlying patterns or structures (Tompkins, 1993). These features can be used for various purposes, such as classifying signals and detecting specific patterns or anomalies. Signal features can be broadly divided into time-domain and frequency-domain features, each offering distinct insights into the signal's properties (Muthuswamy, 2004). Moreover, additional features, such as the time-frequency domain, can be extracted to capture more intricate signal attributes. A comprehensive understanding of these categories and their respective features is essential for proficient signal analysis and processing (Dey, 2016).

2.4.1 Time-Domain Features

Time-domain features are directly derived from the signal in the time domain, offering valuable insights into the signal's amplitude, duration, and temporal structure (Tkach et al., 2010). Unlike frequency-domain features, which require transformation into a different domain, time-domain features maintain the original temporal relationships within the signal (Samuel et al., 2018). This makes them particularly useful for capturing transient events, trends, and other time-related patterns crucial for analysis, classification, and interpretation. By focusing on the inherent properties of the signal over time, time-domain features provide a more intuitive and immediate understanding of the signal's behavior and characteristics (Vidaurre et al., 2009). Table 2.2 lists the commonly used time-domain features, descriptions, and formulae.

Table 2.2 Common Time-Domain Features

Feature	***Description***	***Formula***
Mean	Average value of the signal	$\mu = \frac{1}{N}\sum_{i=1}^{N} x_i$
Variance (Var)	Measure of signal variability	$\sigma = \frac{1}{N}\sum_{i=1}^{N}(x_i - \mu)^2$
Standard Deviation (SD)	Dispersion around the mean	$\mathrm{SD} = \sqrt{\sigma}$
Root Mean Square (RMS)	Magnitude of the signal	$\mathrm{RMS} = \sqrt{\frac{1}{N}\sum_{i=1}^{N} x_i^2}$
Skewness	Asymmetry of the signal distribution	$\mathrm{Skewness} = \frac{1}{N}\sum_{i=1}^{N}\left(\frac{x_i-\mu}{\sigma}\right)^3$
Kurtosis	Tailedness of the signal distribution	$\mathrm{Kurtosis} = \frac{1}{N}\sum_{i=1}^{N}\left(\frac{x_i-\mu}{\sigma}\right)^4$
Zero Crossing Rate (ZC)	Rate of sign changes in the signal	$\mathrm{ZC} = \frac{1}{N-1}\sum_{i=1}^{N-1}\mathbb{I}\{(x_i \cdot x_{i+1}) < 0\}$
Peak-to-Peak Value (PPV)	Difference between max and min values	$\mathrm{PPV} = x_{\max} - x_{\min}$
Crest Factor (CF)	Ratio of peak value to RMS value	$\mathrm{CF} = \frac{x_{\max}}{\mathrm{RMS}}$
Autocorrelation (AC)	Similarity between signal and its lagged version	$\mathrm{AC}(\tau) = \sum_{i=1}^{N} - \tau x_i x_i + \tau$

2.4.2 Frequency-Domain Features

Frequency-domain features represent the signal's frequency components, offering insights into its periodicity, spectral content, and harmonic structures (Srinivasan et al., 2005). Frequency-domain features detect patterns, trends, and regularities that are not readily apparent in the time domain. These features are instrumental in applications such as audio and speech processing, vibration analysis, and biomedical signal analysis, where comprehending the frequency content is essential for effective analysis and interpretation (Altın and Er, 2016). Table 2.3 lists the commonly used frequency-domain features, descriptions, and formulae.

Table 2.3 Common Frequency-Domain Features

Feature	***Description***	***Formula***
Spectral Centroid (SC)	Center of mass of the spectrum	$\mathrm{SC} = \frac{\sum_{k=0}^{N-1} f_k \cdot \lvert X(k)\rvert}{\sum_{k=0}^{N-1} \lvert X(k)\rvert}$
Spectral Bandwidth (SB)	Width of the spectrum	$\mathrm{SB} = \sqrt{\frac{\sum_{k=0}^{N-1} (f_k - \mathrm{SC})^2 \cdot \lvert X(k)\rvert}{\sum_{k=0}^{N-1} \lvert X(k)\rvert}}$
Spectral Flatness (SF)	Flatness or peakiness of the spectrum	$\mathrm{SF} = \frac{\left(\prod_{k=0}^{N-1} \lvert X(k)\rvert\right)^{\frac{1}{N}}}{\frac{1}{N}\sum_{k=0}^{N-1} \lvert X(k)\rvert}$
Power Spectral Density (PSD)	Power distribution across frequencies	$\mathrm{PSD}(f_k) = \frac{\lvert X(f_k)\rvert^2}{N}$
Harmonic Ratios (HR)	Strength of harmonic components	$\mathrm{HR} = \frac{\lvert X(2f_0)\rvert + \lvert X(3f_0)\rvert + \cdots}{\lvert X(f_0)\rvert}$
Spectral Entropy (SE)	Difference between max and min values	$\mathrm{SE} = -\sum_{k=0}^{N-1} P(k) \log P(k)$

2.4.3 Wavelet Transform

Wavelet transforms, are powerful tools in signal processing that offer distinct advantages over traditional Fourier transforms (Bracewell, 1989). The continuous wavelet transform

(CWT) involves breaking down a signal into wavelets - small oscillatory functions localized in both time and frequency domains (Pathak, 2009). This scale-dependent analysis provides a comprehensive view of the signal, enabling the identification of transient features and non-stationary components that are not easily detectable using other methods (Burrus et al., 1998). The CWT is particularly valuable in signal and image processing applications where precise feature localization is essential. The basic expression of CWT is given in Equation (2.1).

$$\mathrm{CWT}(a,b) = \frac{1}{\sqrt{|a|}} \int_{-\infty}^{\infty} x(t)\, \psi^* \left(\frac{t-b}{a} \right) dt \tag{2.1}$$

On the other hand, the discrete wavelet transform (DWT) decomposes a signal into a finite set of wavelet coefficients at various scales and positions (Heil and Walnut, 1989). The DWT is computationally efficient and well-suited for practical applications such as data compression, noise reduction, and feature extraction in digital signal processing (Weeks and Bayoumi, 2003). The multi-resolution analysis capability of the DWT makes it ideal for analyzing signals with varying frequency content over time (Sifuzzaman et al., 2009). The basic DWT expression is shown in Equation (2.2) while it's simplest form, the Haar wavelet is shown in Equation (2.3).

$$\mathrm{DWT}(m,n) = \sum_k x[k]\, \psi_{m,n}[k] \tag{2.2}$$

$$\psi(t) = \begin{cases} 1 & \text{if } 0 \le t < \frac{1}{2}, \\ -1 & \text{if } \frac{1}{2} \le t < 1, \\ 0 & \text{otherwise.} \end{cases} \tag{2.3}$$

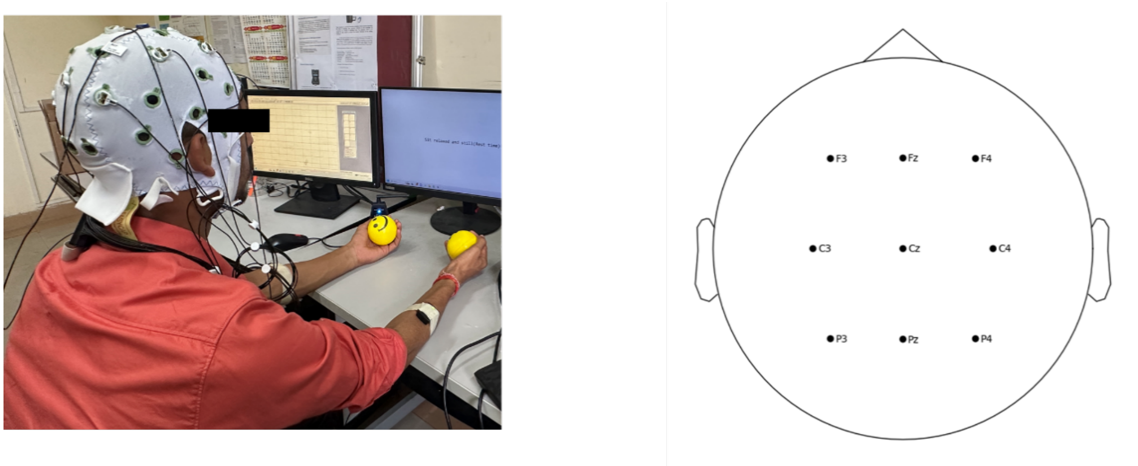
Another standard wavelet used is Daubechies wavelets, denoted as Db. The formula is given in Equation (2.4). Daubechies wavelets (Db) form a family of orthogonal wavelets known for their compact support and different levels of smoothness, which are determined by the number of vanishing moments. They are commonly utilized in signal processing and data compression applications (Lina and Mayrand, 1995; Aljasar and Saqib, 2020).

$$\psi(t) = \sum_{k=0}^{N-1} h_k \phi(2t - k) \tag{2.4}$$

Symlets (Sym) are a modified version of Daubechies wavelets, designed to be symmetrical, which results in improved signal reconstruction while preserving many of the characteristics of Daubechies wavelets. Coiflets (Coif) are another variant that balances smoothness and compact support. They have the added advantage of both the wavelet function and its first few moments vanishing, making them particularly useful in wavelet-based numerical methods. Biorthogonal wavelets (bior) distinguish themselves using two sets of wavelets—one for decomposition and another for reconstruction—enabling perfect reconstruction and linear phase, which is crucial in image processing and compression tasks (Cohen, 1992; Jawerth and Sweldens, 1994).

2.5 Electroencephalography

Electroencephalography is a non-invasive technique used to measure the brain's electrical activity, and it finds wide application in neuroscience, clinical diagnostics, and cognitive science. EEG captures the electrical signals neurons generate using electrodes attached to the scalp (Binnie and Prior, 1994). These signals are amplified and recorded, producing visual representations of the brain's electrical activity as waveform patterns. The EEG procedure consists of several essential steps. Firstly, small metal electrode discs are placed on the scalp using conductive gel or paste (Kiloh et al., 2013). These electrodes pick up the electrical signals generated by the brain's neurons. Since these signals are weak, they require amplification for proper recording. Once amplified, the signals are captured by an EEG machine, which presents the data as waveforms. Figure 2.1 shows the setup of EEG along with electrode placement scheme.



(a) (b)

Fig. 2.1 (a) Experimental Setup. (b) EEG Electrode positions

The frequency ranges of EEG waveforms correspond to specific states of brain activity. Delta waves (0.5-4 Hz) are slow waves associated with deep sleep and certain brain disorders. Theta waves (4-8 Hz) are linked to light sleep, relaxation, and meditative states. Alpha waves (8-13 Hz) are present during relaxed wakefulness, particularly with closed eyes. Beta waves (13-30 Hz) are associated with active thinking, focus, and problem-solving. Gamma waves (30-100 Hz) involve higher cognitive functions like perception and consciousness (Hall and Hall, 2020). The applications of EEG are wide-ranging, especially in clinical diagnostics. In epilepsy, EEG is crucial for diagnosing and monitoring the condition, as it can identify abnormal brain wave patterns indicative of seizures. EEG also plays a crucial role in diagnosing sleep disorders like sleep apnea and narcolepsy by recording brain activity during sleep (Kumar and Bhuvaneswari, 2012). Additionally EEG can evaluate the severity of brain injuries and track recovery, offering valuable insights for patient care and treatment planning (Aminoff, 2012). One of the common applications of

EEG is in Brain-Computer Interfaces and Motor Imagery Tasks. Table 2.4 lists selected publications on applications of EEG.

Table 2.4 Selected publications on applications of EEG

Author (Year)	***Task***	***Model***	***Result***
Al-Asadi et al., (2024)	Emotion recognition	Semi-supervised deep learning	Accuracy: 70%
Balusu and Bhatt, (2024)	Sleep stage classification	Long Short Term Memory Network (LSTM)	Accuracy: 88%
Cheng et al., (2024)	Sleep stage classification	Adversarial Networks	Accuracy: 86%
Hermawan et al., (2024)	Epileptic seizure detection	CNN-LSTM	Accuracy: 91%
Key et al., (2024)	Gaze prediction	Vision transformers	RMSE: 51.6 mm
Trbalić et al., (2024)	Epileptic seizure detection	CNN	Accuracy: 93.58%
Zhao et al., (2024)	Sleep stage classification	U-Net	Accuracy: 85%
Qiu et al., (2023)	Epileptic seizure detection	ResNet-LSTM	Accuracy: 90.17%
Radha et al., (2023)	Prosthetic arm control	Binary Grey Wolf Optimization	Accuracy: 93.6%
Vaquerizo-Villar et al., (2023)	Sleep stage classification	Gradient-weighted Class Activation Mapping (Grad-CAM)	Accuracy: 86.9%
Yogarajan et al., (2023)	Epileptic seizure detection	Binary dragonfly algorithm	Accuracy: 100%
Ibrahim et al., (2022)	Epileptic seizure detection	CNN	Accuracy: 91.28%
Piozin et al., (2022)	Hand motion prediction	Conventional ML Classifiers	Accuracy: 70%
Wang et al., (2022)	Sleep stage classification	Transfer Learning	Accuracy: 87.84%
Tayeb et al., (2020)	Pain perception in prosthesis	Conventional ML Classifiers	Accuracy: 94.66%

2.6 Brain-Computer Interfaces

Brain-computer interfaces (BCIs) combine neuroscience, computer science, and engineering, providing a direct channel for communication between the brain and external devices (Nicolas-Alonso, L.F. and Gomez-Gil, 2012). BCIs convert brain signals into commands that can operate computers, prosthetic limbs, and other assistive technologies, opening new opportunities for individuals with severe physical disabilities and deepening our knowledge of neural processes (Shih et al., 2012). The foundation of BCIs lies in the accurate capture and interpretation of brain signals. This is typically achieved through EEG or invasive methods such as intracortical implants (Dong et al., 2023). EEG-based BCIs employ non-invasive electrodes on the scalp to record electrical activity generated by neurons. These signals are then processed to extract meaningful patterns corresponding to specific mental states or intentions. Invasive BCIs, conversely, involve the implantation of microelectrodes directly into the brain tissue, offering higher-resolution data by capturing the activity of individual neurons (Rouzitalab et al., 2023). BCIs have many potential applications, from aiding individuals with motor impairments to enhancing human-computer interaction and gaming (Tang et al., 2023). In the medical sector, BCIs can help patients with conditions like ALS or spinal cord injuries communicate, use wheelchairs, and operate computers through their thoughts (Chaudhary et al., 2016). They are also being developed for neurorehabilitation to aid stroke survivors in recovering motor functions (Silvoni et al., 2011). In non-medical applications, BCIs allow users to control devices or virtual environments through thought alone, creating a more immersive and intuitive experience (Gao et al., 2021). Additionally, they are being explored for cognitive enhancement, such as improving attention, memory, and learning through neurofeedback and other techniques (Hochberg and Donoghue, 2006). Table 2.5 lists out selected literature in BCI research primarily for motor imagery tasks.

Table 2.5 Advances in BCI Motor Imagery tasks

Author (Year)	*Task*	*Model*	*Result*
Lei et al., (2023)	2 class motor imagery (hand close/open)	Error Related Potentials (ErrP) ERD features + CNN	Accuracy: 73%
Malan et al., (2022)	2 class motor imagery (left, right hand)	Dual Tree Complex Wavelet Transform + SVM	Accuracy: 84%
Riyadi et al., (2021)	4 class motor imagery	Wavelet Packet Decomposition (WPD) + Subtractive Clustering	Accuracy: 68% F1 score: 38%
Chu et al., (2020)	6 class motor imagery	Riemannian Geometry based Tangent Space (TS) features + LDA	Accuracy: 80%
Li et al., (2020)	2 class motor imagery	CWT + SCNN (Simplified CNN)	Accuracy: 83%
Mammone et al., (2020)	2 class premovement motor imagery	LCMV beamformer + CWT + CNN	Accuracy: 63%
Ma et al., (2019)	3 class motor imagery	Multiple channel correlation network	Accuracy: 83%
Yahya et al., (2019)	6 class motor execution	Common Spatial Patterns (CSP) + CWT + pre trained GoogLeNet	AUROC: 0.985
Ofner et al., (2017)	6 class motor execution imagery	Discriminative Spatial Patterns (DSP) + shrinkage regularized LDA (sLDA)	Accuracy: 55% (Execution), 25% (Imagery)
Tavakolan et al., (2017)	3 class motor imagery	Time domain features + SVM	Accuracy: 74 %

2.7 Electromyography

Electromyography (EMG) is a diagnostic technique utilized to measure the electrical activity generated by skeletal muscles (Türker, 1993). EMG involves using surface electrodes to detect the electrical potentials muscle cells produce when these cells are electrically or neurologically stimulated. EMG is widely employed in medicine and research to evaluate and diagnose the condition of muscles and the nerve cells that govern them (Bauwens, 1948). Clinically, EMG plays a crucial role in diagnosing neuromuscular disorders such as ALS, muscular dystrophy, and peripheral neuropathies, as it assists in identifying the source of muscle weakness, paralysis, or twitching. In rehabilitation, EMG biofeedback is utilized to aid patients in regaining muscle control and enhancing motor function after injuries or surgeries (Merletti and Farina, 2016). Further, EMG is significant in sports science for enhancing athletic performance by analyzing muscle activation patterns, enabling athletes to refine their techniques and prevent injuries (Massó et al., 2010). In the ergonomics field, EMG is used in research to gain insights into muscle coordination and motor control in diverse activities, contributing to advancements in prosthetics and the development of advanced human-machine interfaces (Burden, 2007). Table 2.6 lists selected publications utilizing EMG as the primary modality.

Table 2.6 Selected Publications on the Application of EMG

Author (Year)	***Task***	***Model***	***Result***
Anselmino et al., (2024)	Prosthetic leg control	SVM	Accuracy: 95.82%
D'Accolti et al., (2024)	Prosthetic arm control	SVM	Accuracy: 80%
Emimal et al., (2024)	Hand gesture recognition	Ensemble	Accuracy: 91.3%
Gupta and Agarwal, (2024)	Prosthetic leg control	LDA	Accuracy: 94.15%
Kok et al., (2024)	Hand gesture recognition	SVM	Accuracy: 86.97%

Table 2.6 (Continued) Selected Publications on the Application of EMG

Author (Year)	***Task***	***Model***	***Result***
Pourmokhtari and Beigzadeh, (2024)	Hand gesture recognition	KNN	Accuracy: 91%
Suganthi and Rajeswari, (2024)	Prosthetic arm control	LSTM	Accuracy: 96.16%
Xue et al., (2024)	Prosthetic leg control	1D CNN	Accuracy: 91.66%
Yang et al., (2024)	Knee joint angle prediction	CNN	Accuracy: 76%
Zbinden et al., (2024)	Prosthetic arm control	FFNN	Accuracy: 91.6%
Zhang et al., (2024)	Hand gesture recognition	Dynamic time warping	Accuracy: 93.75%
De la Cruz-Sánchez et al., (2022)	Hand exoskeleton control	KNN	Accuracy: 81.2%
Cisnal et al., (2021)	Hand exoskeleton control	Threshold-based control	Accuracy: 97%
Gordleeva et al., (2020)	Lower-limb exoskeleton control	LDA	Accuracy: 78.13%
Sattar et al., (2019)	Prosthetic arm control	ANN	Accuracy: 94%

2.8 Gait Analysis using Electromyography

Electromyography plays a crucial role in gait analysis by providing detailed insights into the muscle activation patterns during walking (Papagiannis et al., 2019). By capturing the electrical activity of muscles, EMG offers direct measurements of the timing and intensity of muscle activation, which is essential for understanding gait biomechanics (Harris and Wertsch, 1994). This valuable information aids in recognizing normal and abnormal gait patterns, diagnosing neuromuscular disorders, and developing effective rehabilitation programs (Chong et al., 1978). During gait analysis, surface EMG sensors are typically positioned on key muscle groups involved in walking, such as the quadriceps, hamstrings, calf muscles, and tibialis anterior. These sensors pick up the electrical signals generated by muscle fibers as they contract and relax during different phases of the gait cycle, including stance (when the foot is in contact with the ground) and swing (when the foot is off the ground) (Kleissen et al., 1998). In clinical settings, using EMG-based gait analysis is vital for evaluating patients with arthritis, stroke, Parkinson's disease, and peripheral neuropathies (Merlo and Campanini, 2016). This technology allows clinicians to pinpoint specific muscular dysfunctions contributing to abnormal gait patterns, thus facilitating targeted interventions. Rehabilitation programs frequently incorporate EMG feedback directly into therapy (Kim et al., 2020). Further, EMG data is vital for developing and refining assistive devices such as prosthetics and orthotics, ensuring that these devices complement the user's natural muscle activity (Freed et al., 2011). Studies utilizing EMG can investigate how different muscles coordinate during gait, the effects of fatigue, and the impact of various interventions on muscle function (Giroux et al., 2013). Table 2.7 highlights the application of EMG in gait analysis.

Table 2.7 Application of Electromyography in Gait Analysis

Author (Year)	***Task***	***Model***	***Result***
Negi et al., (2024)	Gait abnormality classification	CNN	Accuracy: 96.75%
Kumar et al., (2022)	Gait abnormality classification	Recurrent Neural Network	Accuracy: 91.3%
Negi et al., (2022)	Gait abnormality classification	KNN	Accuracy: 99.08%
Popescu et al., (2022)	Gait in Parkinson's disease	CNN	Accuracy: 96.5%
Badura et al., (2021)	Pain state classification	AdaBoost	Accuracy: 85%
Fricke et al., (2021)	Gait abnormality classification	CNN, KNN	Accuracy: 97.3%
Lin et al., (2021)	Human-Robot interface study	CNN	Accuracy: 88%
Xiong et al., (2021)	Gait tracking	PCA and Deep Regression	Accuracy: 87.1%
Zhang et al., (2021)	Multi-modal gait analysis	CNN	Accuracy: 96.05%
Mokdad et al., (2020)	Gait abnormality classification	SVM, LDA, and KNN	Accuracy: 95.8%
Morbidoni et al., (2019)	Gait phase identification	Deep Neural Network (DNN)	Accuracy: 94.9%
Tahafchi and Judy, (2019)	Freezing of gait classification	KNN, Self-Organizing Maps	AUC of 0.91
Le et al., (2018)	Gait analysis	Autoencoder	Accuracy: 96.2%

2.9 Multi-modal EEG-EMG Studies

The simultaneous use of EEG and EMG offers a comprehensive understanding of how brain signals translate into muscle actions, benefiting research and clinical applications (Brambilla et al., 2021). EEG captures the brain's electrical activity through neural oscillations from the scalp, providing detailed insights into the neural processes underlying motor intention and planning (Tryon et al., 2019). The neural signals offer insight into the brain's preparation for movement and the activation of the motor cortex during movement planning. EMG records the electrical signals from muscle fibers during contraction, providing precise information about muscle activation and motor execution (Leerskov et al., 2020). By integrating EEG and EMG, researchers and clinicians can fully trace the pathway from brain motor intention to muscle activity, enhancing our understanding of motor control mechanisms (Lalitharatne et al., 2013). This integrated approach is valuable in applications such as BCIs, neurorehabilitation, and the study of motor control. Integrating EEG and EMG improves the system's ability to detect motor imagery and actual movements, ultimately enhancing responsiveness and accuracy in BCIs (Li et al., 2017). This approach also benefits neurorehabilitation by monitoring both neural intention and physical movement execution, allowing for the customization of rehabilitation protocols and more efficient motor function recovery in patients (Leeb et al., 2011). Moreover, it facilitates the identification of variances between intended and actual movements, which is critical in diagnosing and treating neuromuscular disorders (de Seta et al., 2021). Table 2.8 highlights the selected studies that utilize EEG-EMG in combination.

Table 2.8 Selected publications utilizing EEG-EMG combination

Author (Year)	***Task***	***Model***	***Result***
Alotaibi et al., (2023)	4 class hand movement	Attention-based LSTM	Accuracy: 91%
Fu et al., (2023)	Hand Movement (Grasping and Lifting object)	GCN-LSTM	Accuracy: 89.2%
Lee and Lee, (2022)	13 class overt and imaginary speech classification	EEGNet CNN + Self Attention Module	Accuracy: 49% (overt), 37% (imagined)
Ma et al., (2022)	4 class motor imagery	FBCSP + Time Distributed Attention (TD Atten) + LSTM	Accuracy: 46%
Yang et al., (2022)	4 class hand movement	Graph Convolutional Network (GCN)	Accuracy: 93.86%
Amin et al., (2021)	4 class motor imagery	Attention-based Inception	Accuracy: 94%
Eldele et al., (2021)	5 class sleep stage classification	AttnSleep	Accuracy: 86%
Liu et al., (2021)	3 class emotion classification	3DCANN	Accuracy: 96%
Tryon and Trejos, (2021)	Elbow flexion-extension task weight classification	CNN	Accuracy: 80.51%
Zhou and Zhao, (2021)	Sleep stage classification	CNN	Accuracy: 91.23%

2.10 Machine Learning and Deep Learning

Machine learning (ML) is a rapidly growing field that involves training computers to perform complex tasks with minimal human intervention. In ML, computers learn similarly to humans through experience (Jordan and Mitchell, 2015). The advancements in data science and machine learning have resulted in the development of highly robust systems that tackle complex tasks such as face recognition, self-driving cars, robotics, and prosthetic control (Negi et al., 2022). Machine learning is gradually becoming an integral part of human lives, as many devices and software extensively use it to facilitate complex tasks. Artificial intelligence has made substantial progress in academic and commercial sectors (De Choudhury and Kiciman, 2018). Various areas of machine learning encompass computer vision, speech recognition, natural language processing, and image processing. A variety of algorithms are available to solve complex tasks. These algorithms primarily involve mathematical operations or statistical concepts, which help the machine identify patterns or solutions from the data. (Ayodele, 2010). There are three primary learning approaches: supervised learning, unsupervised learning, and reinforcement learning. In supervised learning, the classifier is provided with class labels and trains itself to correctly identify them based on previous knowledge (Caruana and Niculescu, 2006). Unsupervised learning involves predicting values without class labels (Barlow, 1989). In reinforcement learning, the model is trained through feedback, receiving rewards for correct outputs and punishments for incorrect ones (Sutton and Barto, 2018). The goal of every algorithm is to maximize accuracy while minimizing computation time and errors. Another concept closely related to machine learning is deep learning, which utilizes complex architectures inspired by the human nervous system. These architectures are known as artificial neural networks, with deep neural networks (DNNs) comprising multiple layers of neurons performing various calculations to produce desired results (Zhang et al., 2021). A fundamental machine learning deep learning workflow consists of several steps. Initially, the gathered data undergoes processing and cleaning, and normalization or scaling operations may be utilized to improve data consistency. Subsequently, the dataset is divided into training and testing sets in a predefined ratio, typically 80:20 or 70:30 for training and testing data, respectively. The model is then trained using the training sets, and upon completion of the training, its performance is assessed using an unseen test dataset. Adjustments can be implemented to enhance accuracy and prevent overfitting or underfitting (Negi et al., 2021). Figure 2.2 illustrates the workflow of a machine-learning task.

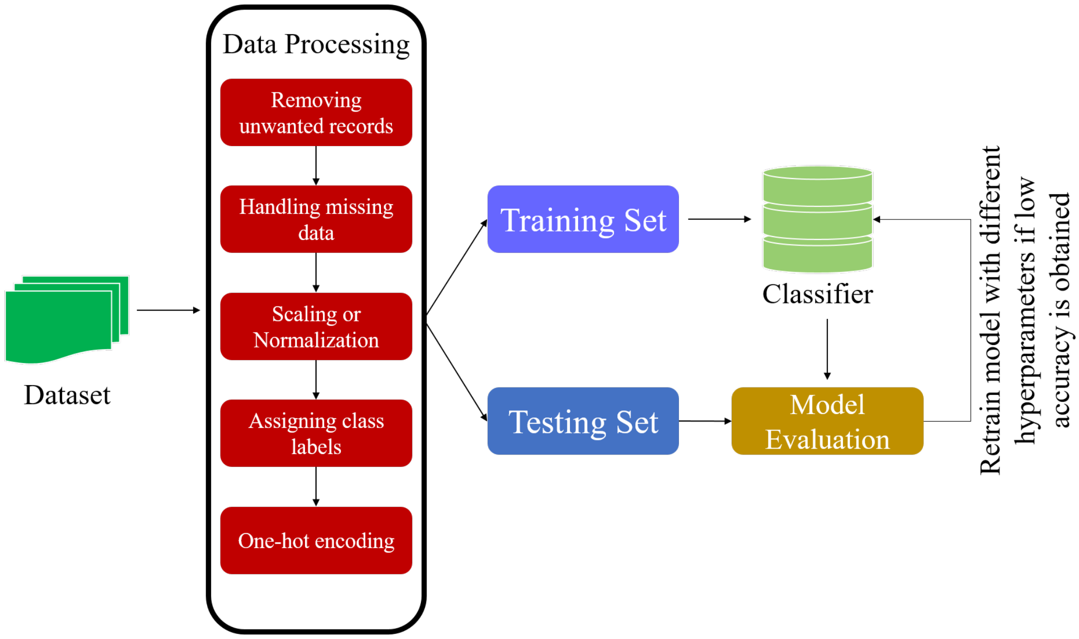


Fig. 2.2 Basic workflow scheme of a machine learning task

2.11 Performance Metrics in Classification

The basis of all classification metrics is the number of True Positives (TP), True Negatives (TN), False Positives (FP), and False Negatives (FN). TP represents instances correctly identified as positive by the model, while TN denotes instances correctly identified as negative. FP signifies instances incorrectly classified as positive, and FN indicates instances mistakenly classified as negative. Accuracy measures the proportion of correctly classified instances among the total instances, providing an overall assessment of the model's performance. Precision evaluates the model's ability to accurately classify positive instances by quantifying the ratio of accurately predicted positives to the total predicted positives. Recall measures the model's capacity to correctly detect positive instances by quantifying the ratio of accurately predicted positives to the total actual positives. The area under the Receiver Operating Characteristic curve (AUC) assesses the model's ability to distinguish between positive and negative classes by analyzing the ROC curve. Lastly, Precision-Recall Coverage (PRC) evaluates the balance between precision and recall across multiple thresholds, making it particularly useful for imbalanced datasets. Table 2.9 briefly highlights the classification metrics used in this study.

Table 2.9 Classification Metrics and Their Formulas

Metric	***Formula***	***Description***
Accuracy	Accuracy = $\frac{TP+TN}{TP+TN+FP+FN}$	Measures the proportion of correctly classified instances out of the total instances.
Precision	Precision = $\frac{TP}{TP+FP}$	Evaluates the model's ability to classify positive instances accurately.
Recall	Recall = $\frac{TP}{TP+FN}$	Assesses the model's capability to identify positive instances correctly.
AUC	Area under ROC curve	Quantifies the model's ability to differentiate between positive and negative classes.
PRC	Precision Recall Coverage	Explores the trade-off between precision and recall across varying thresholds, particularly in imbalanced datasets.